The Effects of International F/X Markets on Domestic Currencies Using Wavelet Networks: Evidence from Emerging Markets

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The Effects of International F/X Markets on Domestic Currencies Using Wavelet Networks: Evidence from Emerging Markets*

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Abstract

This paper proposes a powerful methodology wavelet networks to investigate the effects of international F/X markets on emerging markets currencies. We used EUR/USD parity as input indicator (international F/X markets) and three emerging markets currencies as Brazilian Real, Turkish Lira and Russian Ruble as output indicator (emerging markets currency). We test if the effects of international F/X markets change across different timescale. Using wavelet networks, we showed that the effects of international F/X markets increase with higher timescale. This evidence shows that the causality of international F/X markets on emerging markets should be tested based on 64-128 days effect. We also find that the effects of EUR/USD parity on Turkish Lira is higher on 17-32 days and 65-128 days scales and this evidence shows that Turkish lira is less stable compare to other emerging markets currencies as international F/X markets effects Turkish lira on shorten time scale.

Key Words: *F/X Markets, Emerging markets, Wavelet networks, Wavelets, Neural networks*

JEL classification: C45, F31, G15

1. Introduction

Significant improvements in the communication and usage of computer based analysis techniques in finance have created a complex data flow in the financial markets. Contrary to the past, many domestic economies are open to the international effects in terms of especially

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interest rates and exchange rates. Domestic exchange rates are used to manage the inflation and interest rates, and vice versa.

In promising emerging markets, foreign portfolio investments and hedge funds have great contributions in capital and money markets. However, they import the global effects into the domestic countries as well. Domestic exchange rates are affected by EUR/USD parity both due to trade balance and money flows from foreign portfolio investments. What is more, stability in the advanced economies encourages money flow into the promising emerging markets. Therefore, it is expected that low volatility in the EUR/USD parity might be a factor in low and positive volatility in promising emerging markets.

On the other hand, modelling financial time series in emerging markets requires certain advanced and computer based intelligent methods due to low trade volume, relatively high transaction costs, thin trading and consequently non-linear returns and chaotic behaviours of the participants. Especially in the emerging markets, if the central bank are trouble in reserves, the volatility in the domestic currencies increases due to low volumes of the domestic exchange rates markets.

Due to complex and rapid information flow in global markets and chaotic/volatile environment in emerging markets, modelling exchange rates in emerging markets requires consideration of effects of EUR/USD parity with advanced stochastic models.

The aim of this article is to display the effects of EUR/USD parity on domestic exchange rates in selected promising emerging markets. The importance of the paper comes from its methodology in modelling the financial time series. Due to complex nature of emerging markets, it is stated that computer based intelligent models are more proper to capture the chaotic patterns and non-linear behaviours in the market. Therefore, wavelet networks are selected to capture effects of EUR/USD parity on domestic currencies in three selected promising emerging markets, namely Russia, Brazil and Turkey.

The paper is structured as follows. As a starting point, a literature review on modelling financial markets with neural networks and wavelet networks is introduced. That part includes also a review of research on capturing effects of international F/X markets on domestic currencies by wavelet networks, as well.

In the part of methodology, architectures of both neural networks and wavelet networks are examined in terms of modelling financial markets. Algorithm of feed-forward networks used to train the financial series in the article is discussed in detail, as well. After introducing data used in the wavelet networks training, empirical results are discussed in terms of both theoretical and portfolio management perspectives. Since predicting exchange rates signals a deficit for the efficient market hypothesis, the results might have important theoretical clues for the finance theory, as well.

The paper has some suggestions for future research in the conclusion part. It is stated that the neural networks based models requires theoretical customisation in terms of statistics and research in this paper have some contributions in this perspective.

2. Literature Review

Prediction of fundamental risk factors has crucial importance in developing trading strategies in financial institutions. In emerging markets, exchange rates are one of the determinants in pricing domestic financial instruments issued in money and capital markets. Especially in financial institutions, exchange rates have important effects on financial statements due to open positions and structured finance products in foreign exchanges.

Long-run behaviour of exchange markets is mostly dependent on the macroeconomic factors though in the short-run price-volume correlation and interdependencies among different market segments are important in returns of exchange rates (Campbell, 1997). However, the data on volume of trade is not widely available for F/X markets.

Interdependencies among different market segments, on the other hand, arise due to the fact that the globalization of the financial markets and short-term hot money flows managed by hedge funds. Most of the managers of the hot money follow the movements in the main international F/X markets, namely EUR/USD parity since volatility and price changes in the domestic markets are related to the international exchange rate movements.

However, due to chaotic patterns in the emerging markets, some difficulties occur in modelling financial time series. Due to complex nature of those kinds of markets, conventional forecasting methods are not sufficient in capturing chaotic behaviours. Certain advanced econometric models, such as GARCH models, have been used to model financial variables in developing markets. However, the researches show that pure econometric models are not sufficient to predict the financial variables due to rapid and non-linear data flows in the markets.

In recent years, some "artificial" alternatives have been employed to model market risk factors such as neural networks. The researches display that artificial neural networks are more powerful in forecasting than the econometric models though neural nets need some statistical approvals (Tang et al., 1991). Recent works in the literature show that neural networks have important advantages over econometric models. Since neural nets do not make any assumptions on the normal distribution, the models are not biased. Hidden layers in the network architecture employ the data to develop an internal representation of the relationship among the inputs. Therefore, more proper prediction results can be reached by using neural nets if the relationship among the variables does not fit an assumed model (Ozun, 2006).

Modelling exchange rates by neural networks are great investigation in recent years. By employing weekly data from 1984 to 1995, Yao, Poh and Jasic (1996) forecast the GBP, DEM, CHF, JPY and AUD against the USD and state that models with neural nets create a more proper estimation in returns than ARMA models. By using the single-step and multi-step prediction of the major exchange rates, Carney and Cunningham (1999) display that neural network models make sense of complex data defining traditional analysis.

By employing daily and weekly data, Hu et al. (1999) also show that neural network models have relatively accurate results in predicting exchange rates than regression analysis. Gilbert, Krishnaswamy and Pashley (2000), argue neural networks perform best with incomplete data. They state that since neural networks readjust their weights as new input data, the method is adaptive. By employing random walk, GARCH(1,1), neural networks and nearest neighbours models, Gencay (1999) predict FRF, DEM, JPY, CHF and GBP against a common currency with daily data from 1973 to 1992 and states that non-parametric models outperform parametric models. What is more, he shows that nearest neighbours over performs models based on neural networks as well.

In practice, researches show that neural networks can be useful in creating trade strategies especially if the markets have chaotic patterns. Critiques of neural networks are based on the claim that they are black boxes since none knows how they capture the non-linearities in detail. However, lack of statistical validation of the neural networks, and standardized architectures, integration of neural networks with other statistical or artificial intelligence methods is used to model financial data in recent years. Namely, wavelets and a combination of wavelets and neural networks are deep investigation of the researchers in finance theory.

Wavelets are one of the most promising modelling technologies used in a widespread area of science. In finance, wavelet analysis measures risk at different scales and the flow of volatility from one scale to the other. They are used for the detection of cascade processes. The volatility in return have long-term correlations from large to small time scales (Muzy et al., 2001).

Since in capturing of non-linearities in risk and return relationship, fixed time scales are not enough, a time adaptive approach simultaneously taking all time-scales of the distributions in consideration is need for chaotic dynamics of emerging financial markets. In that respect, architectures of wavelets are localized both in time and frequency-scale while at the same time proper to approximate discontinuities.

By decomposing a signal in two components -mother and father-, namely fine and coarse resolution, wavelets present multiresolutions. Father wavelets are proper to represent the smooth and while the mother ones present high-frequency parts of a signal. In wavelets, a signal is represented as a linear combination of wavelet functions. According to Gencay, Selcuk and Whitcher (2002) a wavelet is like a sine and cosine function which oscillates about zero. However, since oscillations of wavelet fade away about zero, he function is localized in time.

Combination of wavelet analysis with neural networks promises theoretical innovation to solve the statistical drawbacks of the independent models. In fact, there are certain similarities between a perception in neural networks architecture and a wavelet decomposition. Especially a training algorithm for feedback wavelet networks used as nonlinear dynamic models is great importance in modelling financial time series in emerging markets. This paper also employs a feedforward wavelet networks to capture effects of EUR/USD parity on domestic currencies of Russia, Brazil and Turkey which have promising but volatile markets.

Wavelets and neural nets can be combined in different methods. For example, a signal might be decomposed on some wavelets and the coefficients estimated are furnished to a neural network. In other words, the wavelet part might be decoupled from learning. As an alternative, wavelets neural networks are combined into a single method.

Wavelet networks is firstly used by Daugman (1988) for image classification. Wavelet networks are introduced like a special type of feedforward neural network. Zhang (1992) employs wavelet networks for controlling a robot arm.

Wavelet decomposition method is based on the usage of an orthogonal basis consisting of wavelets. The goal in the process is to decompose any signal into a summation of all possible wavelet bases in different scales (Alsberg at al., 1997). Ramer and Kreinovich (1994) states that since there are universal functional estimators representing a function to some precision compactly, wavelet networks promise accurate results in predictions.

In practice, decision on the number of wavelets have problems in wavelet networks. An accurate building wavelet neural networks architecture is important in creating fast convergence of the algorithm. According to Zhang (1992) coefficients with an orthogonal least-squares procedure might be used in the architecture. On the other hand, Echauz and Vachtsevanos (1996) argues an elegant method with trigonometric wavelets. As a training algorithm, Szu et al. (1992) use backpropagation algorithms and conjugate gradient method while stochastic gradient algorithm is used by Zhang (1992). In this paper, feed-forward algorithm is used for training aims. It is also possible to use fuzzy or genetic algorithms for training, as well.

With the usage of wavelet neural networks for financial market predictions has been widely spread. The literature show that chaotic behaviour of financial markets in emerging markets might be well represented by using wavelet neural networks. However, it should be kept in mind that modelling exchange rates with artificial models are more successful in short-term while the models are not accurate in prediction in the long-run currency behaviours. Jamal and Sundar(1997) state that artificial network models have advantages over the econometric models if the exchange rates are predicted for short-term periods.

According to market heterogeneity, different motivations among the players results in sensitivity by the market to different time scales. Müller at al. (1995) state that market heterogeneity is related to fractial behaviour of F/X markets. Shin and Han (2000) explain the fact that in the short-term traders constantly follow the market and execute transactions at a high frequency. On the other hand, long-term traders watch the market less frequently. A rapid price increase followed by a quick fall of the same amount is an important movement for a F/X trader with speculative portfolio while that price movement is non-event forlong-term investors. According to the authors, different kinds of market participants create multiscale dynamics of the financial time series. They conclude that multiscale characteristics of wavelet analysis makes it powerful for detection of scaling behaviours for chaotic patterns.

Before passing through the methodology used in the analysis, it might be useful to underline the fact that the exchange rate dynamics in the long run are affected by fundamental macroeconomic variables and trade partners of the domestic countries, as well. For example, effects of EUR/USD parity on Ruble/USD and Turkish Lira/USD parities are expected to more clear than that of Brazilian Real/USD parity since Russia and Turkey have more trade value with EU while trade of Brazil is more intensive with US. What is more, candidate of membership in the European Union is expected to affect the exchange rate of an applicant country.

In the following part, neural networks and wavelet networks architectures are introduced in detail.

3. Methodology

In this part of the paper, after introducing a framework for neural networks architecture, wavelet networks methodology used in the analysis is discussed in detail. The paper employs a feed forward wavelet networks as training algorithm.

Hertz, Krogh and Palmer (1991) state that neural networks have a similar structure of the brain consisting of nodes passing activation signals to each other. Rumelhart and McClelland (1986) describe the three kinds of nodes namely, an input layer, hidden layer, and an output layer. The data passes from the input layer. The nodes process the information are called as hidden layers, and the layer where an output pattern from a given input pattern processing through the preceding layers is labelled as output layer. The researches show that the number of nodes in each hidden layer can be selected randomly. The number of input nodes, on the other hand, might be chosen on the nonlinear dynamic analysis. However, more than three nodes in the hidden layer produce a neural network that only memorizes the data in input layer.

In design of neural networks, the main stage is to train the network minimizing the error and provide an accurate estimation level. To build a multi-layer neural network, backpropagation algorithm is suggested which compares the output of the processing elements of the output layer to desired outputs for the particular input patterns given. Since hidden layers do not have training target value, they must be trained according to the errors from previous layers. The errors are backpropagated through the nodes, the connection weights change and the training finishes until the errors in the weights are enough small to reach a minimum level.

Feedforward networks have one or more hidden layers of sigmoid neurons and they are followed by an output layer of linear neurons. Multi-layers of neurons with sigmoid or other nonlinear transfer functions lead the network to learn nonlinear relationships among input and output vectors.

Among the certain algorithms, for financial time series, generally feedforward neural network architecture based on backpropagation algorithm is preferred. It is trained fast and the results in capturing random patterns are more accurate in feed forward networks. During training stage, every neuron performs a weighted summation of the inputs passing a nonlinear activation function. When the training ends, its parameters are adjusted until the training data reaches the desired value.

Before explaining wavelet neural networks methodology, it might be useful to explain basic structure of feed forward neural networks. In the financial time series analysis, the inputs of feed forward neural networks consist of a number of delayed observations, while the target is the next value. Since a shift invariant map might be approximated arbitrarily with linear filters feeding a neural network, feed forward neural networks might be not enough to capture the dynamics of a non-stationeries in the system. Therefore, a data driven adaptation of the weights that backpropagate information between the neurons is required. A neural network is detected as a mapping network if it computes functional relationship between inputs and output.

In the following, after discussing theoretical foundations of wavelet neural networks, dynamic feed forward wavelet networks used in this paper are introduced in detail.

Wavelets theory is based on Fourier analysis whisch is any function can be represented with the sum of sine and cosine functions. Fourier analysis or fourier series can be represent as Equation (1).

$$f(x) = b_0 + \sum_{k=1}^{\infty} b_k \cos 2\pi kx + a_k \sin 2\pi kx \tag{1}$$

$$b_0 = \frac{1}{2\pi}\int_0^{2\pi} f(x)\,dx \quad , \quad b_k = \frac{1}{\pi}\int_0^{2\pi} f(x)\,Cos(kx)\,dx \quad , \quad a_k = \frac{1}{\pi}\int_0^{2\pi} f(x)\,Sin(kx)\,dx$$

a_0, a_k *and* b_k can be solved with OLS. Fourier to wavelet transition is given Equation (2).

$$f(x) = c_0 + \sum_{j=0}^{\infty} \sum_{k=0}^{2^j-1} c_{jk}\psi(2^j \chi - k) \tag{2}$$

$\psi(x)$ called as mother wavelet which is mother to all dilations and translations of ψ in Eq.(2). A simple example of mother wavelet is (Tkacz, 2001) in Equation (3).

$$\Psi(x) = \begin{cases} 1 & : 0 \le x < \frac{1}{2} \\ -1 & : \frac{1}{2} \le x < 1 \\ 0 & : other \end{cases} \tag{3}$$

In high frequency finance the maximal overlap discrete wavelet transform (MODWT) is used instead of DWT as MODWT can handle any sample size N and wavelet variance estimator of MODWT is asymptotically more efficient than the estimator based on the DWT.

The MODWT is formulated with matrices (Gencay at all, 2002 and Percival and Walden, 2000) and yields J vectors of wavelet filter coefficients $\tilde{W}_{j,t}$, for j=1,…,J and t=1,….,N/2^j, and one vector of wavelet filter coefficients $\tilde{V}_{j,t}$ through(Gallegati, 2005) Eq. (4) and (5)

$$\tilde{W}_{j,t} = \sum_{l=0}^{L_{j-1}} \tilde{h}_{j,l}\, f(t-1) \tag{4}$$

$$\tilde{V}_{j,t} = \sum_{l=0}^{L_{j-1}} \tilde{g}_{j,l}\, f(t-1) \tag{5}$$

Where $\tilde{h}_{j,i}$ and $\tilde{g}_{j,l}$ are the scaled wavelet and scaling filter coefficients.

Fig. 1 shows the structure of wavelet networks. Wavelet networks consist of two parts as wavelet and neural networks. Firstly, wavelet is estimated for inputs and outputs, secondly each of these inputs and outputs are estimated with feed forward neural networks.

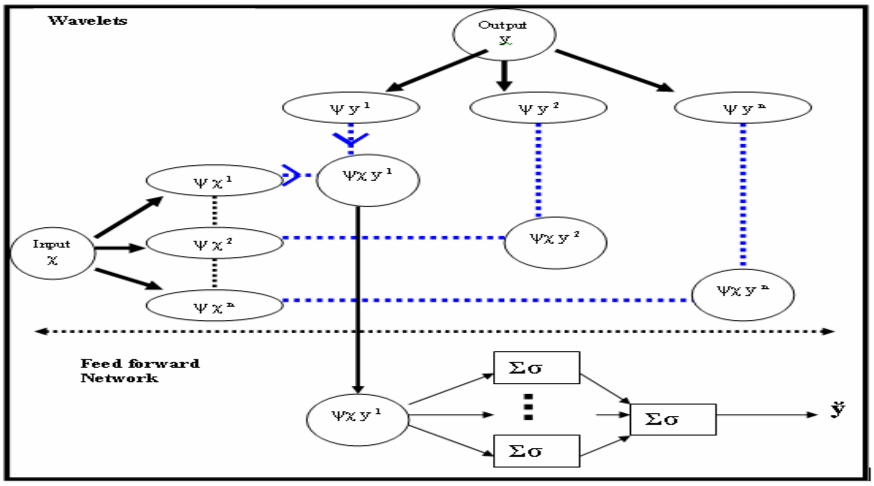
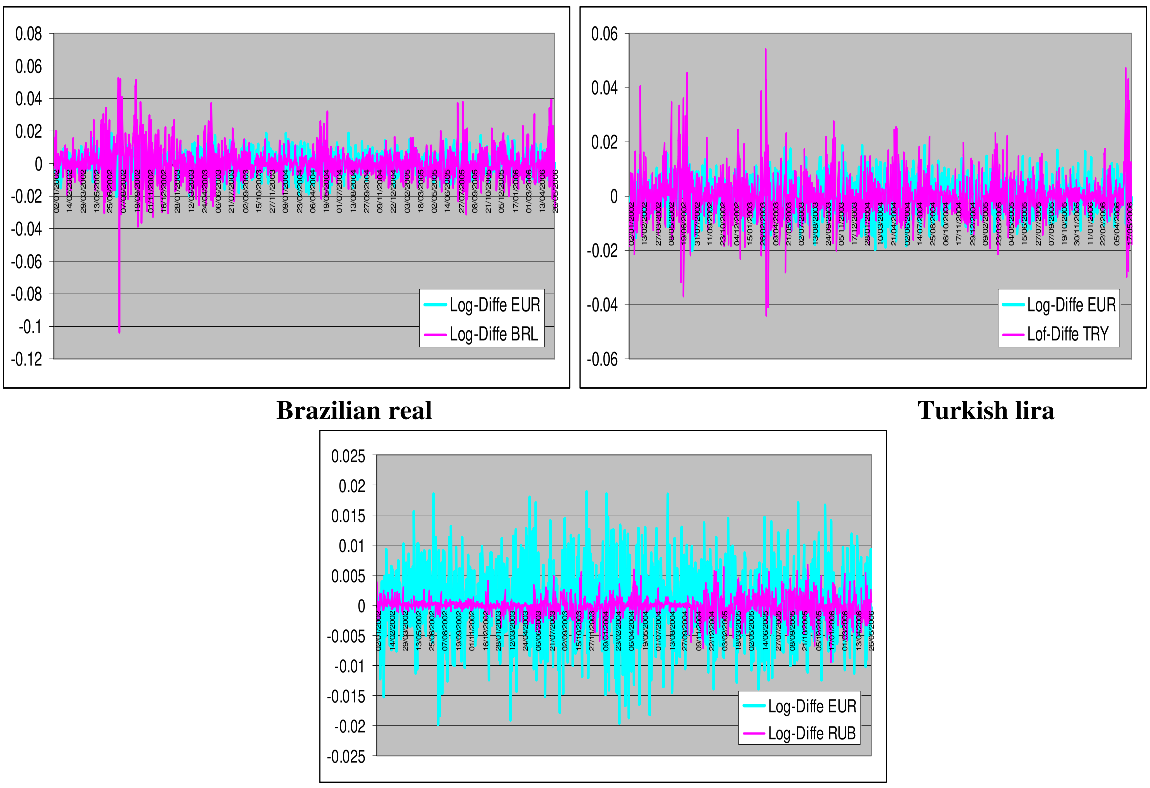


Fig. 1. The Structure of Wavelet Networks

4. Data and Empirical Results

Data

Emerging markets exchange rates as Brazilian real/USD, Turkish lira/USD and Russian ruble/USD as well as the EUR/USD parity are from Bloomberg. Our dataset covers 1151 daily observations from 02/01/2002 to 31/05/2006. We analyzed the effect of EUR/USD rates on emerging market exchange rate on univariate case and we constituted the series in levels, logarithmic and log-differenced. Fig. 2 shows three emerging markets currencies versus Eur/Dollar rate in log-differenced series.



Brazilian real **Turkish lira**

Russia ruble

Fig. 2. Log-differenced series (Eur and emerging market currency)

Empirical Results

We study, using data from 2002 to 2005, the stationarity properties of three emerging markets rates and EUR/USD rate by performing augmented Dickey–Fuller (Dickey and Fuller, 1981) tests for all the time series. The results of the unit root tests in Table 1 shows that all of the level and log variables are not stationary whereas they are all stationary at their log differenced level.

Table 1
Unit root test statistics of the time series

	ADF Test	
Variables	nl	**t-stat.**
EUR	0	-1.65363{<0.9}
BRL	2	-1.20707{<0.9}
TRY	1	-1.57124{<0.9}
RUB	0	0.594046{<0.99}
In EUR	0	-1.75131{<0.9}
In BRL	2	-1.09696{<0.9}
In TRY	1	-1.59441{<0.9}
In RUB	0	0.628901{<1}
Δ In EUR	0	-36.1166{<0.01}*
Δ In BRL	1	-26.2713{<0.01}*
Δ In TRY	0	-38.3423{<0.01}*
Δ In RUB	0	-32.9094{<0.01}*

Notes. Tests for prices in level use a constant but not a time trend. The table reports results of the augmented Dickey–Fuller (Dickey and Fuller, 1981) tests for all the time series. The number of lags (nl) in the tests have been selected using the Schwarz information criterion with a maximum of twelve lags. Probability of the statistic exceeding the computed value under H_0 is given in braces.
* Indicate the rejection of the unit root null at the 1% significance level.

Cointegration test results in Table 2 shows that according to Johansen cointegration test (Johansen, 1991 and 1995) and Engle-Granger ADF test (Engle and Granger, 1987) all of the emerging markets rates are co integrated with EUR/USD rate.

Table 2
Cointegration test results

	Unrestricted Cointegration Rank Test			E-G ADF Test	
		Trace Stat.	**Max-Eigen Stat.**	**nl**	**test stat.**
Δ In EUR & Δ In BRL	r=0	162.485 {<0.01}*	90.5797 {<0.01}*	1	-26.319
	r≤1	71.9048 {<0.01}*	71.9048 {<0.01}*		{<0.01}*
Δ In EUR & Δ In TRY	r=0	149.074 {<0.01}*	93.3024 {<0.01}*	0	-38.825
	r≤1	55.7716 {<0.01}*	55.7716 {<0.01}*		{<0.01}*
Δ In EUR & Δ In RUB	r=0	158.175 {<0.01}*	93.7383 {<0.01}*	0	-33.9403
	r≤1	64.4368 {<0.01}*	64.4368 {<0.01}*		{<0.01}*

* indicates significance of cointegration at the 1 % level.

Firstly, we estimate wavelets with 6 scales as 1-4 days, 5-8 days, 9-16 days, 17-32 days, 33-64 days and 65-128 days based on MODWT Multiscale analysis. Fig. 3 shows the estimated series scale by scale analysis.

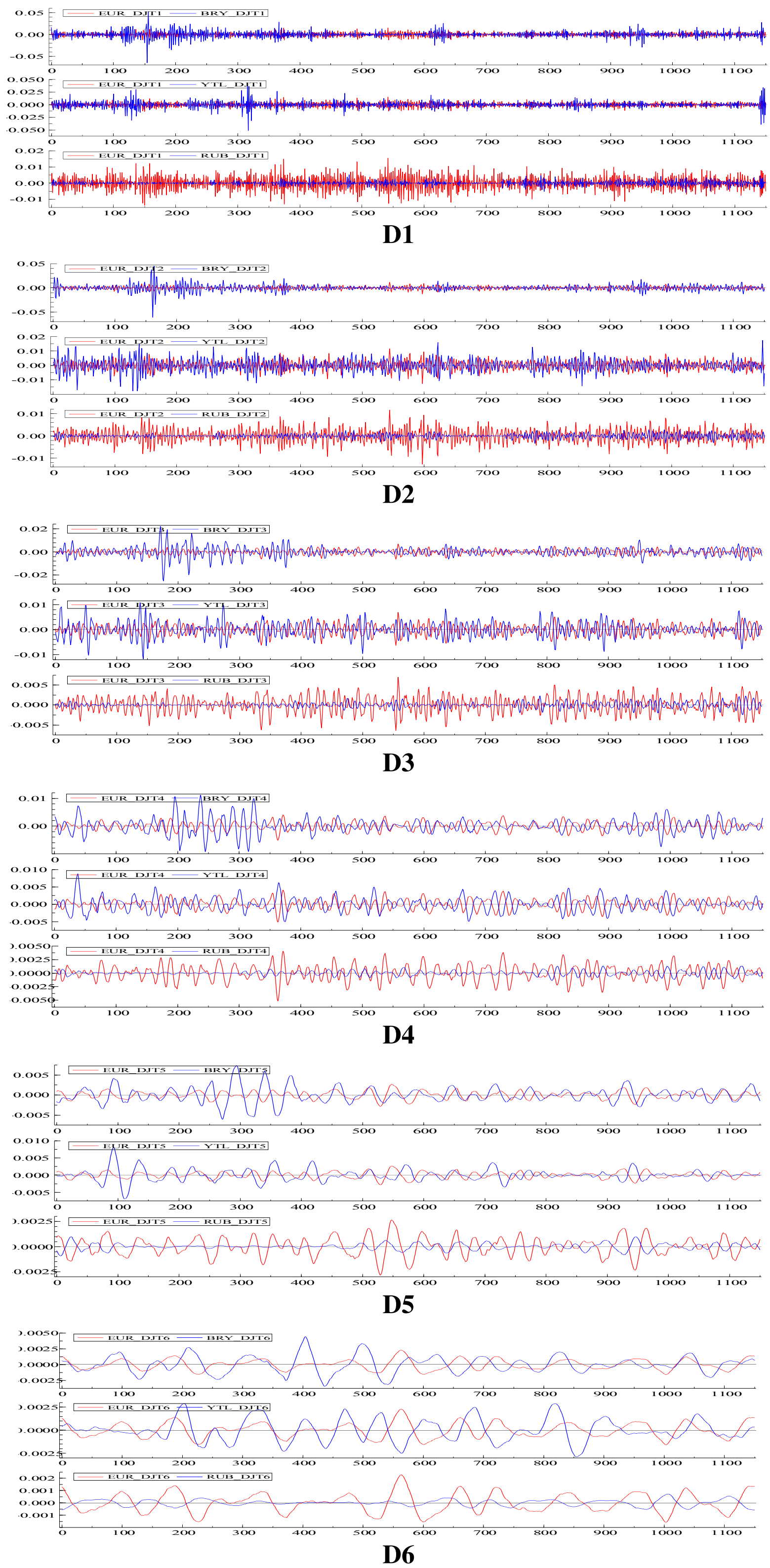


Fig. 3. Wavelets with 6 Scales*

** D1, D2, D3, D4, D5 and D6 represents 1-4 days, 5-8 days, 9-16 days, 17-32 days, 33-64 days and 65-128 days scale respectively. First line is Brazilian real and eur, second line is Turkish lira and eur and third line is Russian ruble and eur respectively.*

We test if all the scaled series are stationary with ADF Test. The results of the unit root tests in Table 3 shows that all of the level variables are stationary. Since all the variable are stationary, wavelet networks can be estimate.

Table 3
Unit root test statistics of the scaled time series

	ADF Test	
Variables	nl	**t-stat.**
Δ In EUR_DJT1	7	-30.641{<0.01}*
Δ In BRL_DJT1	7	-23.8888{<0.01}*
Δ In TRY_DJT1	7	-30.471{<0.01}*
Δ In RUB_DJT1	7	-21.001{<0.01}*
Δ In EUR_DJT2	7	-29.9315{<0.01}*
Δ In BRL_DJT2	7	-32.6731{<0.01}*
Δ In TRY_DJT2	7	-32.1542{<0.01}*
Δ In RUB_DJT2	7	-29.9983{<0.01}*
Δ In EUR_DJT3	5	-31.2656{<0.01}*
Δ In BRL_DJT3	6	-19.3287{<0.01}*
Δ In TRY_DJT3	5	-28.77{<0.01}*
Δ In RUB_DJT3	6	-21.202{<0.01}*
Δ In EUR_DJT4	7	-8.35007{<0.01}*
Δ In BRL_DJT4	7	-8.24651{<0.01}*
Δ In TRY_DJT4	7	-8.63349{<0.01}*
Δ In RUB_DJT4	7	-8.62572{<0.01}*
Δ In EUR_DJT5	7	-9.53897{<0.01}*
Δ In BRL_DJT5	7	-13.4063{<0.01}*
Δ In TRY_DJT5	6	-11.8454{<0.01}*
Δ In RUB_DJT5	6	-11.3662{<0.01}*
Δ In EUR_DJT6	6	-8.31426{<0.01}*
Δ In BRL_DJT6	6	-8.01818{<0.01}*
Δ In TRY_DJT6	7	-6.92953{<0.01}*
Δ In RUB_DJT6	6	-7.33268{<0.01}*

Notes. The table reports results of the augmented Dickey–Fuller tests for all the time series. The number of lags (nl) in the tests have been selected using the Schwarz information criterion with a maximum of twelve lags. Probability of the statistic exceeding the computed value under H_0 is given in braces.
* Indicate the rejection of the unit root null at the 1% significance level.

Table 4 shows correlation matrix of Emerging Markets currencies with international F/X rate as EUR/USD rate based on scale by scale analysis. All scaled series are correlated negatively with EUR/USD Dollar rate and correlation levels change according to scale for different emerging markets currencies. The maximum correlation of Russian ruble is %54.452 at scale 6, Turkish lira is %41.981 and Brazil real is %14.031. This evidence shows that Russian ruble is mostly affected from international F/X market according to multiscale correlation analysis.

Table 4
Correlation Matrix

	EUR_DJTX
BRY_DJT1	-0.05541
BRY_DJT2	-0.08269
BRY_DJT3	-0.11359
BRY_DJT4	**-0.14031**
BRY_DJT5	-0.00560
BRY_DJT6	0.068296
YTL_DJT1	-0.15386
YTL_DJT2	-0.21607

YTL_DJT3	-0.33656
YTL_DJT4	**-0.41981**
YTL_DJT5	-0.02353
YTL_DJT6	-0.04375
RUB_DJT1	-0.23161
RUB_DJT2	-0.33072
RUB_DJT3	-0.43034
RUB_DJT4	-0.31430
RUB_DJT5	-0.39576
RUB_DJT6	**-0.54452**

We estimate one hidden layer neural network as input is international F/X rate and output is emerging market currency with wavelet network analysis as shown in Fig. 1. Table 5 shows that MSE decreasing with higher scales except Turkish lira and MSEs are minimum for Russian ruble and this evidence is compatible with multiscale correlation analysis as shown in Table 4.

Table 5
Wavelet Networks

	MSE (training set)	MSE (test set)	R^2	Correlation
BRY_DJT1	4,731E-05	0,0001278	-0,0133	0,1603
BRY_DJT2	3,186E-05	5,824E-05	0,0281	0,2397
BRY_DJT3	1,285E-05	2,439E-05	0,0619	0,2725
BRY_DJT4	6,026E-06	9,144E-06	0,0642	0,2960
BRY_DJT5	3,435E-06	3,878E-06	0,0477	0,2862
BRY_DJT6	1,625E-06	1,617E-06	0,0909	0,3352
YTL_DJT1	4,004E-05	5,277E-05	0,0810	0,3236
YTL_DJT2	1,424E-05	2,553E-05	0,0549	0,2821
YTL_DJT3	6,091E-06	1,156E-05	0,1151	0,3736
YTL_DJT4	2,527E-06	4,303E-06	**0,2183**	0,4826
YTL_DJT5	2,255E-06	4,718E-06	0,0657	0,2975
YTL_DJT6	1,212E-06	1,729E-06	0,0921	0,3836
RUB_DJT1	1,311E-06	1,31E-06	0,1022	0,3741
RUB_DJT2	6,181E-07	6,79E-07	0,1704	0,4485
RUB_DJT3	2,793E-07	3,005E-07	0,2197	0,4953
RUB_DJT4	1,46E-07	1,672E-07	0,1628	0,4342
RUB_DJT5	5,962E-08	8,994E-08	0,2538	0,5114
RUB_DJT6	3,996E-08	4,121E-08	**0,3431**	0,5899

Fig. 4, Fig. 5 and Fig. 6 shows graphical analysis of Table 5 for Brazilian real, Turkish lira and Russian Ruble respectively. MSE is minimum at Scale 4 and Scale 6 for Turkish lira where MSE is minimum at Scale 6 for Brazilian real and Russian ruble. R^2 is also maximum at scale 4 for Turkish lira. Besides, MSE decreasing as scale increases except Turkish lira. This evidence shows that Turkish lira effected from international F/X market around one month and six month frequency.

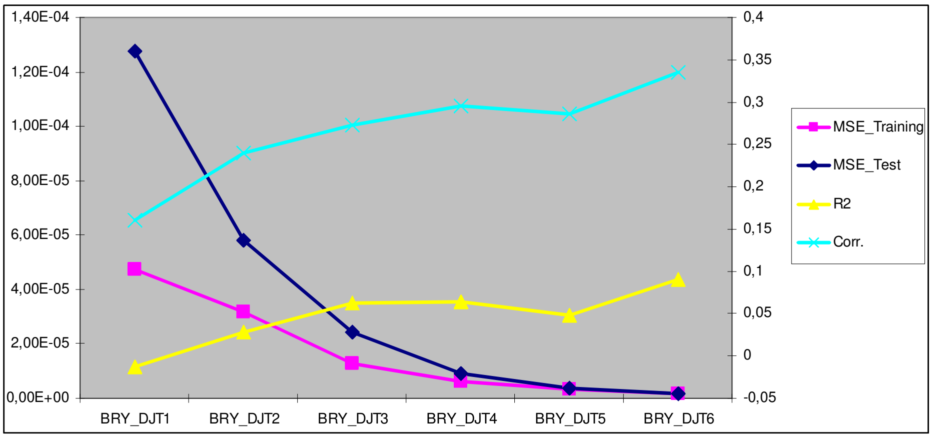


Fig. 4. Wavelet Networks (Brazilian real)

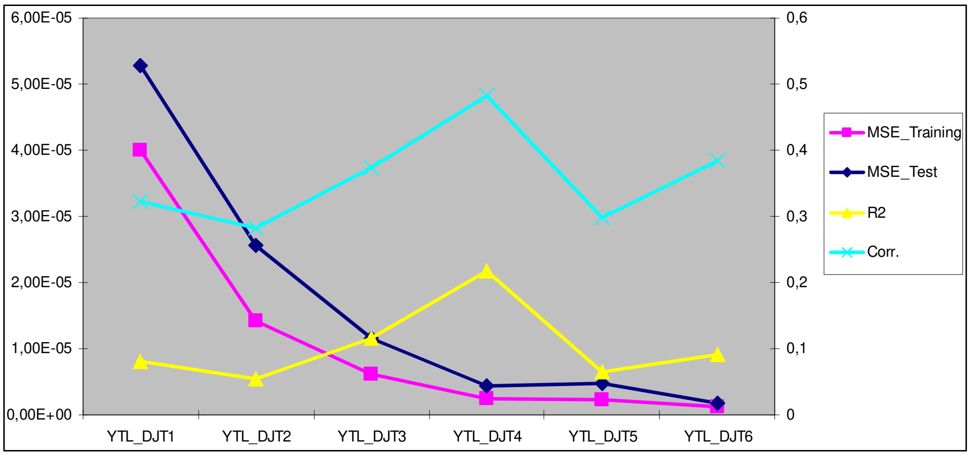


Fig. 5. Wavelet Networks (Turkish lira)

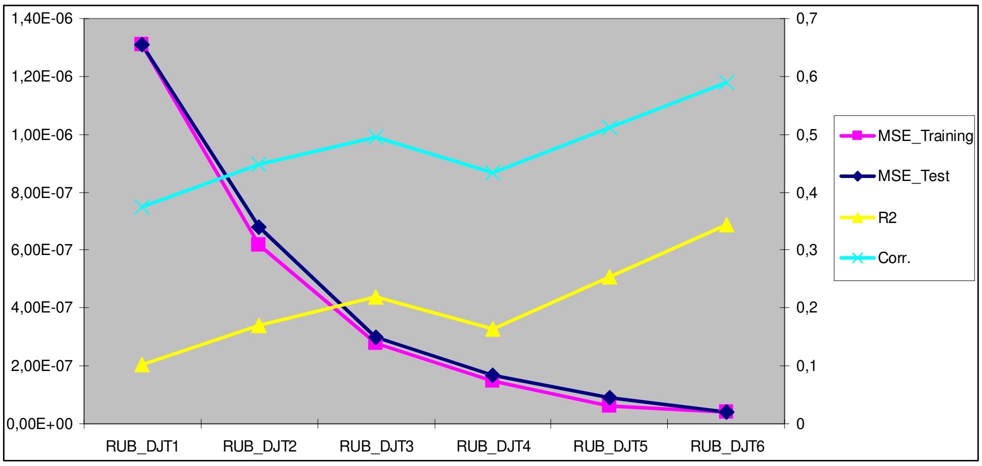


Fig. 6. Wavelet Networks (Russian ruble)

5. Conclusion

Due to fast and intensive money flows from developed countries into emerging markets, developments in international markets have global effects on emerging financial markets. In that respect, it is expected that volatilities in international F/X markets have some importance on domestic exchange rates in emerging markets. Since portfolio investments into emerging markets require a certain degree of stability in advanced economies, it si expected that volatilities in EUR/USD parity has negative impact on domestic currencies in emerging markets.

By using a powerful methodology, namely wavelet networks, this paper examines the effects of international F/X markets on emerging markets currencies. We used EUR/USD parity as input indicator and three emerging markets currencies as Brazilian Real, Turkish Lira and Russian Ruble as output indicator (emerging markets currency) in separate analysis. We test if the effects of international F/X markets change across different time-scales.

It is clearly displayed that the effects of international F/X markets increase with higher timescale on domestic currencies. The empirical evidence shows that the causality of international F/X markets on emerging markets should be tested based on 64-128 days effect. The paper has important findings for Turkish markets, as well. It is found that the effects of EUR/USD parity on Turkish Lira is higher on 17-32 days and 65-128 days scales, which displays the fact that Turkish Lira is less stable compare to other emerging markets currencies as international F/X markets effects Turkish lira on shorten time scale.

On theoretical side, the paper shows that intelligent systems, like wavelet networks, are useful to capture chaotic patterns in emerging markets. The future research might concentrate on combination and comparison of intelligent systems and econometric models to reach alternative modeling techniques.

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